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Original scientific paper

A Grey Wolf Optimization Based Approach to Provide Ancillary Services for Battery Owners

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Abstract: As is known, batteries have started to be used increasingly in both power distribution and transmission networks. This study develops a near-optimal approach for ancillary services in power networks from the perspective of the battery owner. We first model the optimization algorithm for the battery owner, then utilize a grey wolf optimization approach, where near-optimal actions are selected daily from available services. We use real data of frequency, voltage magnitude, combined home and Photovoltaic system, and transformer load to perform the simulations. The simulation results show that battery owners may profit from these services and help the system operators solve the issues such as over-voltage, under-voltage, frequency, and similar.

Keywords: Ancillary services, Batteries, Optimization, Grey wolf optimization.

1 Introduction

Integrating distributed, intermittent, and variable renewable energy sources (RESs), especially in power distribution networks, has increased the risk of under/overvoltage, frequency problems, and other operational issues. This drives a change of the conventional fit-and-forget approach in the integrating new assets into the distribution networks. In parallel, control capabilities are increasing with innovative functions available in recently developed power electronics-based inverters, battery energy storage systems, EV chargers, etc. Battery energy storage systems have been used more frequently in the last decade since they have extensive power up and down-regulation capabilities, can store surplus

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Colour versions of the one or more of the figures in this paper are available online at https://sjee.ftn.kg.ac.rs production from PV, or can be charged when energy prices are relatively lower than usual (or even when there are negative prices that foster demand increment) and can be discharged when PV production is low or at peak, high price periods [1, 2].

The battery costs are still high, even with a significant decrease since 2010 of over 85% due to technological advancements and economies of scale [3]. The trend is expected to continue since innovations in battery chemistry, such as solid-state batteries, and manufacturing efficiencies will further reduce production expenses [4]. Despite the reduced initial capital costs, operational costs such as battery degradation and maintenance expenses need to be considered, and these costs were analyzed for using second-life EV batteries for stationary energy storage [5].

Battery owners may earn additional profits by providing flexibility services; however, challenges such as battery degradation, regulatory frameworks, and operational optimization may negatively influence their profitability. For instance, in [6], the authors state that the battery degradation costs should be managed efficiently to have sustained profitability. If appropriately applied, the strategies to mitigate wear and tear during high-demand periods may improve economic outcomes.

Many scientific publications recognize the importance of batteries in ancillary services. Recently, battery usage for daily market participation and energy dispatch optimization models have shown improved profit margins for battery owners [7]. In [8], the authors analyzed the impact of different regulatory and market designs on battery owners' profitability by comparing different ancillary service market structures in Great Britain, Texas, and Sweden. Plug-in electric vehicles (PEVs) can provide spinning reserve and frequency regulation services, as analyzed in [9], showing their potential to enhance grid resilience while offering revenue opportunities for PEV owners. In [10], the authors found that by submitting optimized bids for charging and discharging, battery owners can provide reserve capacity efficiently if the policy frameworks to support market participation are available. Another study [11] looks at the economic viability of battery storage systems for ancillary services to optimize the power network performance, considering battery degradation and dynamic market conditions. The batteries' life cycle is optimized while they deliver multi-functional services, including ancillary services in [12].

In this study, we aim to investigate the provision of multiple flexibility services from the perspective of a battery owner to maximize their profitability. We assume that the market structure allows the battery owners to select an ancillary service to contribute at any time step. This will allow the battery owner to decide on an ancillary service (if the stored power is sufficient) and profit from the service. For this, a coordinated strategy should be designed considering degradation. In our proposed model, during the simulation period, the State of Charge (SoC) level is not allowed to go beyond 80% and less than 20%, and by the end of the whole (selected a one-day) simulation period, our model aims to come to the same initial SOC level.

The problem is modeled as an optimization problem. The optimization problems can be solved using derivative or non-derivative-based methods. From those, the derivative-based optimization methods are widely used in power system applications; however, they have some limitations. For example, these methods are inefficient in handling non-convex and multi-modal problems, those which can be encountered in power system related problems [13]. They are also sensitive to initial conditions, [14] making them less robust, and they may converge to local optimum points where the solution spaces are nonlinear [15]. In [16], the authors specified the limitations in coordinating control mechanisms within distribution networks.

Thus, scientists have developed non-derivative heuristic methods to overcome the abovementioned limitations. Genetic Algorithm (GA), developed in the 1970s by Holland [17], was one of the first methods that mimicked the evolution process from nature, using probabilistic mechanisms like selection, crossover, and mutation. In the 1990s, methods like Particle Swarm Optimization (PSO) mimicked the coordinated food search behavior of bird flocks and fish schools [18]. The Harmony Search Algorithm (HSA) uses the improvisation process of jazz musicians to find a better musical harmony, which is analogous to finding a better solution to optimization problems [19]. Similarly, Differential Evolution (DE) uses evolutionary strategies to solve optimization problems by applying recombination, mutation, and selection processes [20]. Unlike derivative-based methods, heuristic methods are not constrained by the need for differentiable objective functions, which are hard to obtain in the case of complex objective functions and are easier to implement.

Other studies [21 – 25] propose multi-service optimization of BESSs across European markets using the Mixed Integer Linear Programming (MILP) algorithm. In [21], combining the Day Ahead Market (DAM) and Frequency Containment Reserve (FCR) markets performs the highest profit, with the perfect-information scenario reaching \$1635/MW-day, which is 527.6% more than the DAM-only case. Similarly, [22] demonstrates that full-service provision using active power control brings up to £897 per day more than reactive power control approaches. The Swedish market case [23] analyses FCR in regular operation (FCR-N), in disturbances (FCR-D) for up- (FCR-DU) and down- (FCR-DD) regulation, and in multi-FCR cases. The multi-FCR yields the most profit with an annual amount of 707.9 k€ while considering battery degradation. The study in [24] compares the constraint levels as well: Independent Chance Constraints (ICC), Boole's Rule, and Improved (Joint Chance Constraints - JCC) with five different markets. The most profitable case is the revenue of the JCC case in the total market with 10,997.69€. Lastly, [25] compares the conventional operation and direct/opposite reserve between different markets and confirms that DAM + FCR stacking yields the best annual revenue with €1.45M for a BESS with 10MW power and 10MWh capacity in the proposed formulation. The revenue of the proposed formulation is 22.8% more than the conventional operation.

The proposed model for the battery owners in this study was solved using an improved version of a recently developed heuristic method, the Grey Wolf Optimization Algorithm (GWO) [26], which simulates the hunting behaviors of the wolves. Up to now, GWO has been applied to several optimization problems in power distribution network problems. For instance, it was utilized without requiring derivative information to effectively coordinate the tap changers, bank capacitors, and PV inverters [16]. Other applications include microgrid design [27], demand side management [28], charging station allocation [29], and similar.

In this paper, we model the battery owner participation in ancillary services as an optimization problem and solve it using a modified grey wolf optimization algorithm. Our contributions are briefly summarized below.

– We propose a mathematical model for battery owners to participate in ancillary services, including voltage and frequency regulation, transformer demand/load regulation.
– We utilize a grey wolf optimization algorithm, considering the integer variables by making proper adjustments to the grey wolf optimization algorithm.
– We test the optimization model using real market and system data and report the results. Thus, the battery owners make a profit, and the system operator may be able to solve power network issues.

The rest of the paper is organized as follows. Section 2 explains the optimization formulation and constraints. Section 3 details the adaptation of the Grey Wolf Optimization method. Section 4 provides the details of data preparation. Section 5 presents the simulation results, and the last section concludes the paper by evaluating the findings and providing pathways to potential future studies.

2 Model

We aim to maximize the revenue of the battery owners while ensuring their contribution to ancillary services. Moreover, we want the aging of the battery not to be impacted, so for this aim, the optimization model is designed to keep the SOC (state of the charge) of the battery at the same level at the start and the end of the simulation period (i.e., the beginning and end of the day).

Our approach defines the prices for various ancillary services over the simulation period, structured as a 24x6 matrix. Each row corresponds to the simulation hour, while each column represents a specific ancillary service: the first column denotes the price for frequency regulation services, the second column represents the price for voltage regulation, and the third column captures the load regulation price for the transformer. The fourth column reflects the idle state, which has no associated cost; the fifth column represents the charging price for the battery; the sixth column accounts for the transfer of excess energy generated by the PV system to the battery.

The mathematical model for optimizing the revenue of the battery owners can be given below.

$$\underset{w.r.t\ \vec{x}}{\text{maximize}}\, \mathrm{F} = \mathrm{P}(\vec{\boldsymbol{x}}) + \mathrm{E}(\vec{\boldsymbol{x}}), \tag{1}$$

where $\mathrm{P}(\vec{\boldsymbol{x}})$ and $\mathrm{E}(\vec{\boldsymbol{x}})$ are given as:

$$\mathrm{P}(\vec{\boldsymbol{x}}) = \sum_i \boldsymbol{g}_i(\vec{\boldsymbol{x}})\boldsymbol{h}_i(\vec{\boldsymbol{x}}), \tag{2}$$

$$\mathrm{E}(\vec{\boldsymbol{x}}) = \mathrm{SoC}_{\max} Capacity_{\max} + \sum_i \boldsymbol{h}_i(\vec{\boldsymbol{x}}) + k_i \tag{3}$$

$$\text{Constraints}: \begin{cases} \mathrm{SoC}_{\min} \le SoC_{present} \le \mathrm{SoC}_{\max}, \\ \vec{\boldsymbol{x}}^{\boldsymbol{lb}} \le \vec{\boldsymbol{x}} \le \vec{\boldsymbol{x}}^{\boldsymbol{ub}}. \end{cases}$$

In (1) – (3), i represents the simulation hour, and $\vec{\boldsymbol{x}}$ is the decision vector, composed of the decision actions of the battery owner on ancillary services (such as contribution to voltage regulation, frequency regulation, and so on). With $\mathrm{P}(\vec{\boldsymbol{x}})$ we show the profit of the battery owner in US dollars. $\mathrm{E}(\vec{\boldsymbol{x}})$ shows the amount of energy (kWh) difference between the start and end of the simulation period (day), k_i represents the excess PV energy generated at hour i, $\boldsymbol{g}(\vec{\boldsymbol{x}})$ represents the price (\$/kWh) obtained for provided service, and $\boldsymbol{h}(\vec{\boldsymbol{x}})$ represents the energy (kWh) that the battery gained or lost. Considering battery aging, a battery with a maximum capacity ($Capacity_{\max}$) of 13.5 kWh is used. The initial state of charge (SoC) at the start of the day is set to 80%. Ensuring that the battery SoC stays at a minimum of 20% and a maximum of 80% also prevents possible deep discharging and overcharging that can significantly negatively impact battery life. The suitable operation range depends on battery chemistry and application. While an SoC range of 20% to 80% is recommended for $LiFePO_4$ batteries [30] and NMC batteries [31], 10% to 90% [32] and even 0% to 90% SoC [33] operation is preferred for LTO batteries, preferably up to 50% Depth of Discharge (DoD) is suggested for Lead-Acid batteries [34], up to 100% discharge is allowed for NiCd, NiMH batteries [35], Ni-Zn batteries [36] and Ni-Fe batteries [37].

2.1 Grey Wolf Optimization algorithm

Grey Wolf Optimizer (GWO) [26] is a meta-heuristic optimization algorithm miming grey wolves' steps while hunting. The process involves searching for prey, encircling it, chasing, hunting, and finally attacking. Grey wolves follow a hierarchical structure, where the α wolf acts as the leader responsible for decision-making and management, supported by the β and δ wolves. Another type of wolf is ω which is tasked with the search phase of the process. Mathematically, these roles can be represented as the best solution, second best solution, third best solution and the remaining ones for alpha, beta, delta, and omega wolves, respectively.

Briefly, the GWO follows the following processes, as given in the subsections below.

2.1.1 Encircling Prey

Wolves surround the prey by updating their positions relative to the prey. This is mathematically represented in (4 – 7) below.

$$\vec{\boldsymbol{D}} = \left|\vec{\boldsymbol{C}}\vec{\boldsymbol{X}}_{\boldsymbol{prey}}(iteration) - \vec{\boldsymbol{X}}(iteration)\right|, \tag{4}$$

$$\vec{\boldsymbol{X}}(iteration+1) = \vec{\boldsymbol{X}}(teration) - \vec{\boldsymbol{A}}\vec{\boldsymbol{D}}, \tag{5}$$

$$\vec{\boldsymbol{A}} = 2\vec{\boldsymbol{a}}\vec{\boldsymbol{r}}_1 - \vec{\boldsymbol{a}}, \tag{6}$$

$$\vec{\boldsymbol{C}} = 2\vec{\boldsymbol{r}}_2. \tag{7}$$

In (4) and (5), $\vec{\boldsymbol{X}}_{\boldsymbol{prey}}$ and $\vec{\boldsymbol{X}}$ represent the best position of the prey (best solution found until that iteration) and the current position of the wolf, respectively. $\vec{\boldsymbol{D}}$ shows the distance between the prey and the wolf, (6) and (7) show how the coefficient vectors $\vec{\boldsymbol{A}}$ and $\vec{\boldsymbol{C}}$ can be calculated by using two random vectors, $\vec{\boldsymbol{r}}_1$ and $\vec{\boldsymbol{r}}_2$, ranged between 0 and 1 and using a linearly decreasing vector $\vec{\boldsymbol{a}}$ from 2 to 0 over the iterations.

2.1.2 Hunting

In hunting phase, the new position is calculated based on the combination of the distances of α, β and δ wolves to the prey as given below in (8) – (13)

$$\vec{\boldsymbol{D}}_{\boldsymbol{\alpha}} = \left|\vec{\boldsymbol{C}}_1\vec{\boldsymbol{X}}_{\boldsymbol{\alpha}} - \vec{\boldsymbol{X}}\right|, \tag{8}$$

$$\vec{\boldsymbol{D}}_{\boldsymbol{\beta}} = \left|\vec{\boldsymbol{C}}_2\vec{\boldsymbol{X}}_{\boldsymbol{\beta}} - \vec{\boldsymbol{X}}\right|, \tag{9}$$

$$\vec{\boldsymbol{D}}_{\delta} = \left|\vec{\boldsymbol{C}}_3\vec{\boldsymbol{X}}_{\delta} - \vec{\boldsymbol{X}}\right|, \tag{10}$$

$$\vec{\boldsymbol{X}}_1 = \vec{\boldsymbol{X}}_{\alpha} - \vec{\boldsymbol{A}}_1\vec{\boldsymbol{D}}_{\alpha}, \tag{11}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2\vec{D}_\beta, \tag{12}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3\vec{D}_\delta. \tag{13}$$

Then the value of the new iteration $\boldsymbol{X}$ vector is calculated as the mean of $\vec{X}_1$, $\vec{X}_2$ and $\vec{X}_3$.

2.1.2 Attacking Prey

In the attacking prey phase, $\vec{a}$ is linearly reduced from 2 to 0, and $\vec{A}$ decreases. If the value of $\vec{A}$ is between –1 and 1, the next position will be between the current position and the prey's position; if not, the value of $\vec{A}$ is randomly selected in the allowed range.

3 Solution of the Model Using Grey Wolf Optimization

We solve the proposed model by utilizing GWO. Initially, GWO randomly creates the positions of the search agents. Note that, in a 24-hour simulated case, for each hour, the algorithm will decide one action from the possible action space: help in frequency regulation, voltage regulation, help on the transformer power demand side, stay idle, or charge itself. Each action is represented by an integer from 1 to 5. Every best solution candidate $\vec{x}$ has a corresponding energy and price/energy value $h_i(\vec{x})$ and $g_i(\vec{x})$ for every hour. We use (1) to evaluate the fitness value of every position $\vec{x}$. This approach is used for daily optimization as a first step for the providing multiple flexibility services that batteries can provide, and the long-term impact of multiple services provision can be further investigated in future studies.

The SoC value is checked at every iteration to comply with the SoC constraint. If the result of the choice made by the GWO violates the SoC constraint, the choice for that specific hour is changed to 'idle' to ensure that the SoC of the battery stays within the limits throughout the day.

We modified the GWO algorithm to align with the abovementioned integer-constrained optimization model. The initialization process generates initial values within the permissible ranges, ensuring they are integers. Any position value calculated as a real number is rounded to the nearest integer within the allowed ranges during the exploration and exploitation phases. The fitness function is subsequently evaluated using these integer-adjusted positions.

The algorithm of the implementation of GWO on battery optimization problem is given in Algorithm 1. In Fig. 1 we give the steps of the algorithm's pseudo-code.

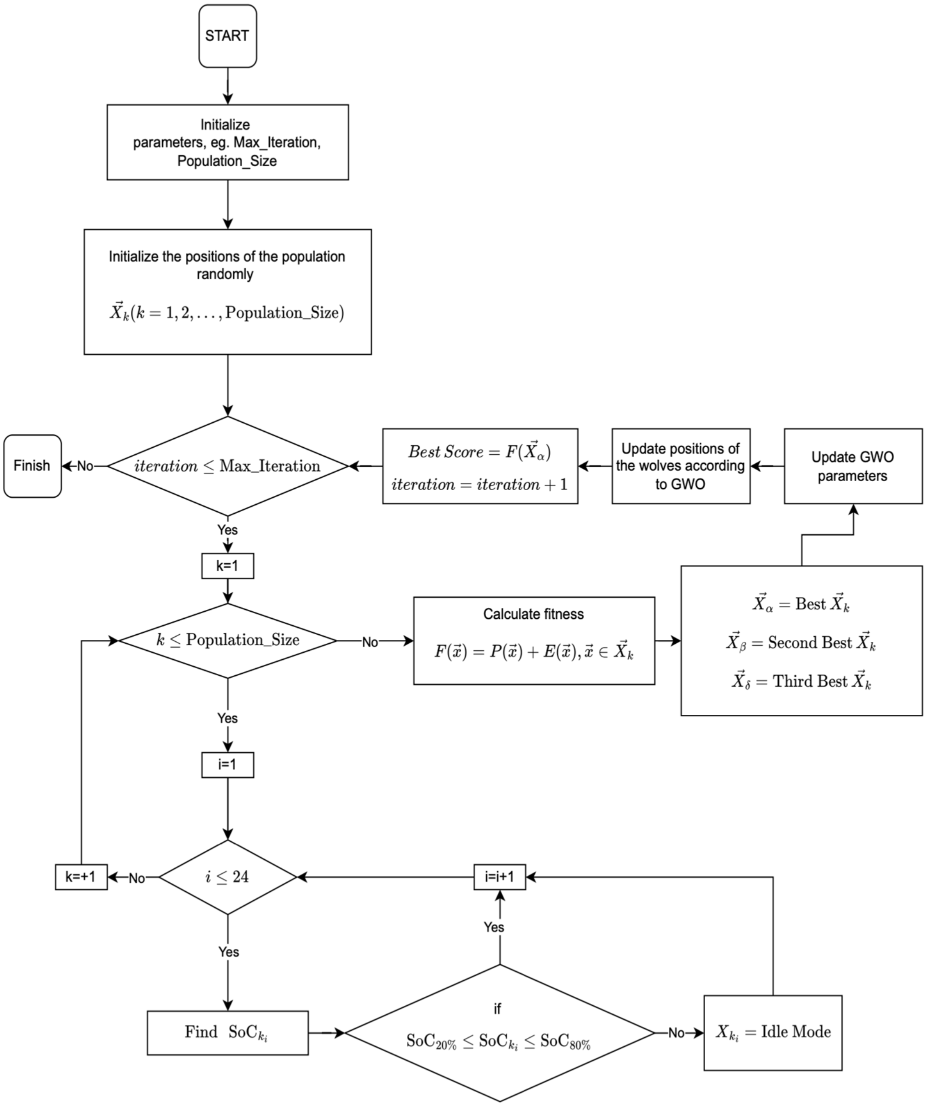

Fig. 1 – *The flow chart of the proposed GWO Algorithm.*

Algorithm 1: Optimization of the SOC of the battery and maximize revenue

Initialize number of search agents
Initialize *l*, a, A, and C
Initialize search agents' positions $\vec{X}_k\left(k = 1, 2, \ldots, num\_search\_agents\right)$
while (*l*<Max number of iteration) **do**
  for each search agent **do**

if search agent out of bounds, **then**
Update search agent positions
end if
end for
for each search agent **do**
Initialize $\boldsymbol{SoC}_{k_0}$ =80%
for i=1 to 24 **do**
Calculate $\boldsymbol{SoC}_{k_i}$ using $\boldsymbol{h}_i\left(\vec{\boldsymbol{X}}_k\right)$
if $\boldsymbol{SoC}_{k_i}$ out of bounds **then**
$\vec{\boldsymbol{X}}_{k_i}$ = Idle Mode
end if
end for
Calculate $\boldsymbol{F}\left(\vec{\boldsymbol{X}}_k\right)$ using *eq.1*
end for
Update a, A, and C
Update $\vec{\boldsymbol{X}}_\alpha, \vec{\boldsymbol{X}}_\beta$, and $\vec{\boldsymbol{X}}_\delta$ positions
l=l+1
end
Best Position = $\vec{\boldsymbol{X}}_\alpha$

4 Data Preparation

According to the relevant studies in the literature and prominent research conducted in this area of study, as summarized in [38], batteries can provide up to 13 services to 3 stakeholder groups (customers, utility operators, and market operators). Based on the pioneering works, market availabilities, and profitability, we focused on our study the multiple provisions of the ones that are more likely to be commonly preferred in real-world applications in many countries, which are frequency regulation, voltage support, congestion relief, energy arbitrage, and increased PV self-consumption. Multiple provision of a larger variety of services can be investigated in future studies. All the events that require flexibility services based on charging or discharging the battery are identified using real frequency, voltage, and power measurements from the field, considering operational constraints (upper and lower frequency deviation thresholds, upper and lower voltage deviation thresholds, and substation loading threshold) to activate flexibility services. Other considered actions are staying idle or charging itself for the battery. We used one-hour resolution data over a day for each service mentioned above. Preparation steps for the data are given in Fig. 2.

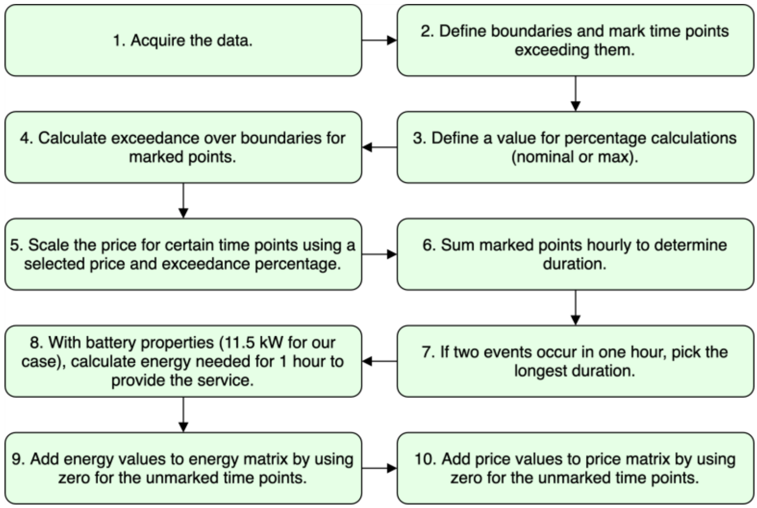

Fig. 2 – *Data Preparation Flowchart.*

We used the National Grid system dataset for power demand data, specifically the Nechells 11kV BSP Transformer Flows dataset [39] in 30-minute resolution. This dataset provides information on the MW power demand from the transformer and the voltage level at the secondary winding. We applied the procedure in the flowchart in Fig. 2 and set the high demand threshold as 80% of the annual maximum of 23.26 MW. We use power demand data from Great Britain for the 7th of February 2023, the day with the most extended duration of high demand, with a total duration of 1 hour. In Fig. 3, we illustrated the hourly power demand for this specified day, using a red line to highlight the values that exceeded the threshold values.

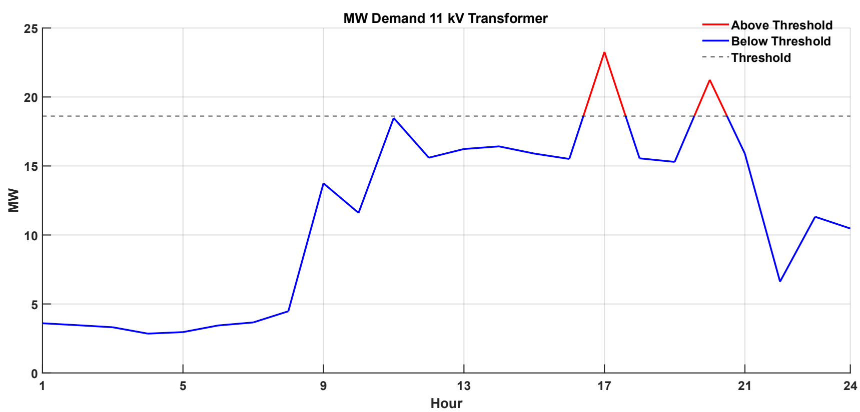

Fig. 3 – 11 kV *Transformer Demand Data.*

We obtained the system frequency data from the National Energy System Operator (NESO) data portal [41] for the year 2024 for the UK. When we picked the high and low-frequency boundaries as 50.2 Hz and 49.8 Hz, respectively, we focused on the following dates, figures of which are given in Fig. 4.

– The day with the most extended duration of high-frequency: 9th of April 2024, 484 s.
– The day with the most extended duration of low-frequency: 19th of October 2024, 524 s.
– The day with the average duration of high-frequency: 30th of May 2024, 42 s.
– The day with the average duration of low-frequency: 14th of June 2024, 62

In Fig. 4, the red lines indicate the high and low-frequency values out of the allowed ranges.

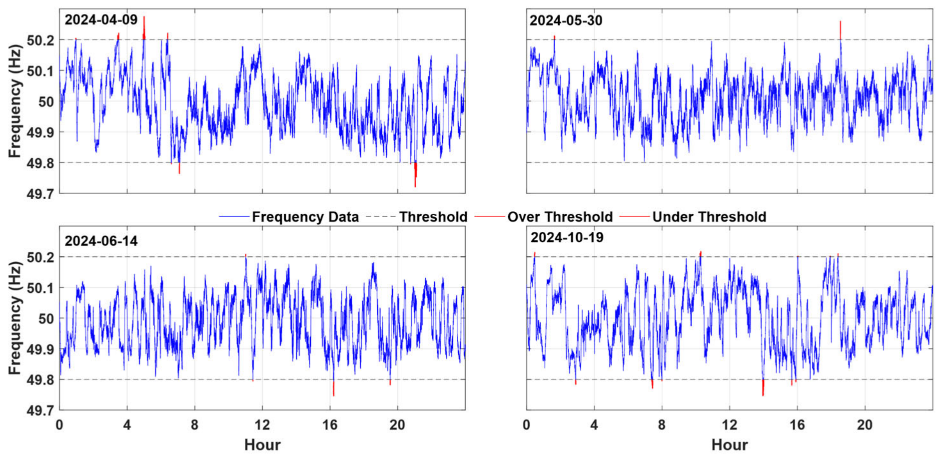

Fig. 4 – *Frequency Data for different days in 2024.*

We utilized Nechells 11 kV BSP Transformer Flows voltage values [39] in 30-minute resolution for voltage regulation service. By setting the overvoltage limit by 3% [40] of 11 kV, we focused on the following dates and showed their voltages in Fig. 5.

– The day with the high duration of overvoltage: 28th of April 2022, 12.5 h.

– The day with the average duration of overvoltage: 3rd of June 2022, 3 h.

This data was also converted to one-hour resolution.

We generated the dwelling demand power data with PV generation from the CREST (Centre for Renewable Energy Systems Technology) Integrated Domestic Electricity Demand and PV Micro-generation Model [42], a macro coding in Excel to generate PV power output, and dwelling power demand. Using the toolbox requires setting parameters such as the number of residents in the house, whether the simulated day is a weekday or a weekend, and so on. We simulated one home with two residents and several electrical devices at home; a PV with a maximum power of 1 kW is assumed to be connected as well. Fig. 6 visualizes the combined load and PV generation data daily.

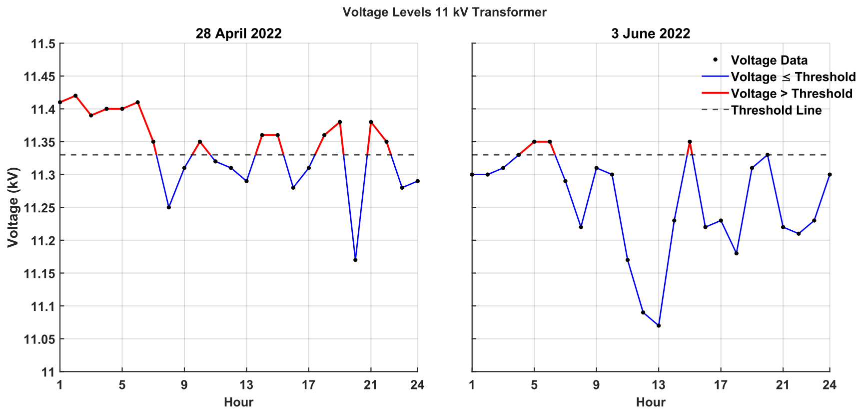

Fig. 5 – *Transformer Voltage Data for 28th of April 2022, and 3rd of June 2022.*

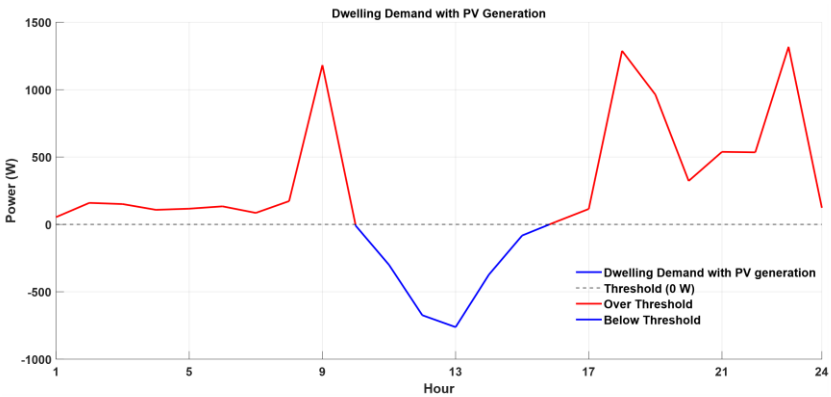

Fig. 6 – *Dwelling Demand Power Data with PV Generation.*

After performing the steps in Fig. 2, Primary Frequency Control (PFC) [43] data are taken from the EPIAS Transparency Platform for 2024. We found the maximum price to be 9450 TL/MWh and scaled it down to 0.249 \$/kWh, picking the currency rate as 1 USD = 38 Turkish Liras. Using 0.249 \$/kWh, every event is scaled according to the exceedance percentage.

Realistic operational costs are considered using real frequency regulation market prices, and their scaled adaptation for voltage regulation and transformer congestion management services to quantify daily profitability. When the battery decides to charge itself for that hour, we assumed that it would reach up to 70%, leaving 10% room for further PV generation. This charge amount goes up to 80% for the last two hours of the day. This is because electricity prices are lowest during the last two hours of the day. For the battery charging prices, we use the three-time residential tariff schedule published by the Turkish Energy Market Regulatory Authority (EPDK) in July 2023 [44]. Daily pricing is as follows. 1.96 TL/kWh for the morning period (06:00-12:00), 3.15 TL/kWh for the afternoon period (12:00–17:00), and 4.62 TL/kWh for the evening period (17:00–22:00). Using the same conversion value, the prices were scaled to 0.0518, 0.0829 and 0.1216 $/kWh as shown in Fig. 7, respectively.

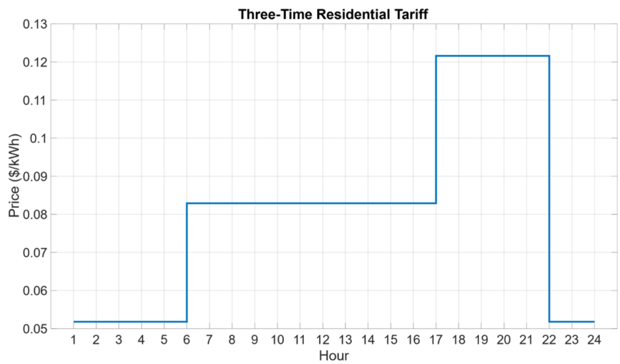

Fig. 7 – *Three-Time Residential Tariff.*

Like Fig. 7, we show the prices for frequency regulation based on two different days by converting the amounts to USD by multiplying each frequency exceed time instant by 0.249 in Fig. 8.

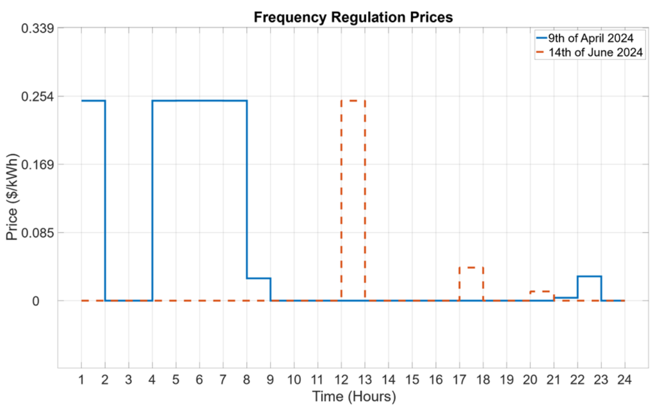

Fig. 8 – *Frequency Regulation Prices for Given Dates.*

We assumed the battery power to be 11.5 kW and multiplied the event duration to calculate the required energy to provide frequency regulation, as shown in Fig. 9.

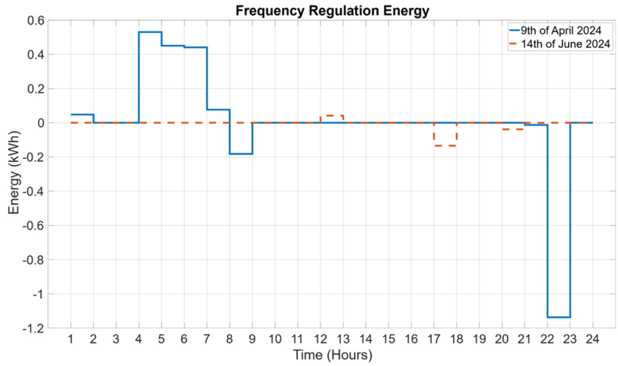

Fig. 9 – *Energy Needed to Provide Frequency Regulation for Given Dates.*

Voltage regulation prices are shown in Fig 10, and the converted USD amounts are used as given above. In Fig. 11, we assumed that the battery power is 5.75 kW to prevent full discharge in one hour. We multiplied the event duration to obtain the required energy to provide voltage regulation for the specified days.

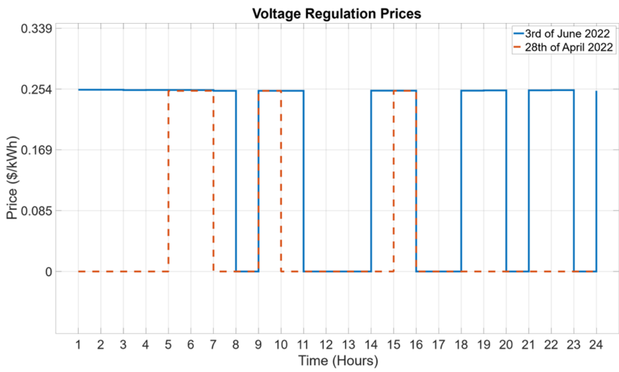

Fig. 10 – *Voltage Regulation Prices for Given Dates.*

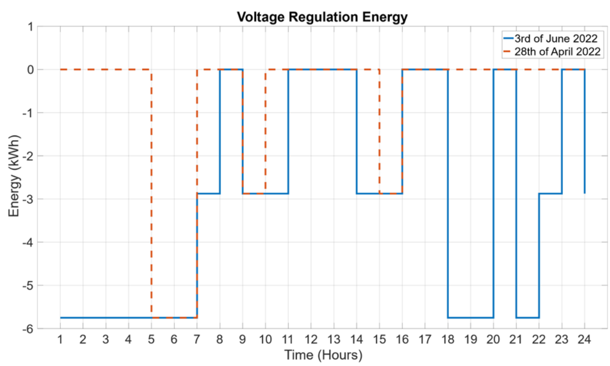

Fig. 11 – *Energy Needed to Provide Voltage Regulation for Given Dates.*

A similar approach was used to construct price values for demand regulation, as given in Fig. 12. Moreover, we assumed the battery power to be 5.75 kW as before to construct the required energy for demand regulation as given in Fig. 13.

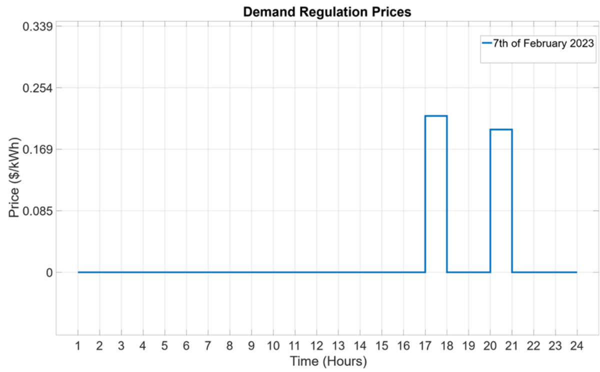

Fig. 12 – *Demand Regulation Prices for Given Dates.*

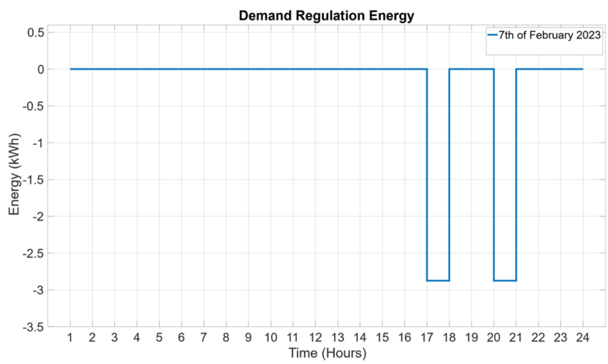

Fig. 13 – *Energy Needed to Provide Demand Regulation for Given Dates.*

5 Simulation Results

Simulations were performed on a MacBook Pro with the Apple M2 chip (10-core CPU, up to 3.49 GHz), 16 GB of unified RAM, and macOS Sequoia (64-bit). We conducted all tests using the proposed GWO algorithm in Matlab with the following parameters: number of search agents: 50, maximum number of iterations: 2,000,000. All other parameters were set to the default values mentioned above.

We simulated extreme and average conditions using different price and energy matrices. The specifications of these simulation cases are explained below.

– Case 1: In this case, frequency service on the 9^{th} of April 2024 (where we have over-frequency for the longest time), voltage service on the 3^{rd} of June 2022, and demand service on the 7^{th} of February 2023 are selected. This case represents an extreme one with long event durations.
– Case 2: We selected the 19^{th} of October 2024, 3^{rd} of June 2022 and 7^{th} of February 2023 for frequency (low frequency for longest time), voltage and demand services, respectively. This case is also an extreme one with long event durations.
– Case 3: We selected the 30^{th} of May 2024 for frequency service, the 28^{th} of April 2022 for voltage service, and the 7^{th} of February 2023 for demand service for this case, which represents an average case for event durations.
– Case 4: In this case, the 14^{th} of June 2024 for frequency service, the 28^{th} of April 2022 for voltage service, and the 7^{th} of February 2023 for demand service are selected. This case represents an average day for event durations.

Due to limited space, we provide only the price and energy matrices for Case 1, as shown below in **Tables 1** and **2**.

A comparison of the numerical results using different numbers of search agents and iterations can be seen in **Table 3**, where cost values are the averages of cost (objective function) values of ten simulations found by the GWO algorithm. We observed that, as expected, increasing the number of search agents decreased the number of different results. We also observed that the algorithm could always find the same numerical result by using a high number of maximum iterations such as 2,000,000. The convergence curve of the objective function for 250000 iterations is given in Fig. 14.

Although the results are consistent in repeated runs with 2,000,000 iterations, this may not ensure convergence to a global optimum. However, the stability across repeated runs indicates a robust near-optimal solution.

The simulations were performed from the perspective of a battery owner. The battery has a total energy capacity of 10.8 kWh when partially charged (80% SoC). In the simulations, we assumed a 24-hour case from the perspective of the battery owner. Based on the condition of the power market explained above, the battery owner decides to contribute to available ancillary services based on the GWO-based optimization approach.

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The GWO algorithm presents an approach independent from topology; as the number of batteries increases, the expected computational time will also increase. However, since the model assumes that these prices are either known or predicted the day before, even with many batteries, the simulation environment will work in time.

To compare the results of taking part in single or multiple ancillary services, cases represented as A, B, and C are created.

– Case A: Only frequency control service, 9th April 2024, is selected for frequency values.
– Case B: Only voltage control service, 3rd June 2022, is selected for voltage magnitudes.
– Case C: Only transformer congestion management (demand regulation) service, 7th February 2023, is selected for demand values.

Table 1
Price Matrix for Ancillary Services Provided by the Battery for Case 1.

Frequency Regulation [$/kWh]	Voltage Regulation [$/kWh]	Transformer Power Demand Regulation [$/kWh]	Idle [$/kWh]	Recharge [$/kWh]
0.2484	0.2480	0.0000	0.0000	0.0518
0.0000	0.2480	0.0000	0.0000	0.0518
0.0000	0.2476	0.0000	0.0000	0.0518
0.2484	0.2477	0.0000	0.0000	0.0518
0.2485	0.2477	0.0000	0.0000	0.0518
0.2485	0.2476	0.0000	0.0000	0.0829
0.2484	0.2466	0.0000	0.0000	0.0829
0.0277	0.0000	0.0000	0.0000	0.0829
0.0000	0.2466	0.0000	0.0000	0.0829
0.0000	0.2466	0.0000	0.0000	0.0829
0.0000	0.0000	0.0000	0.0000	0.0829
0.0000	0.0000	0.0000	0.0000	0.0829
0.0000	0.0000	0.0000	0.0000	0.0829
0.0000	0.2468	0.0000	0.0000	0.0829
0.0000	0.2468	0.0000	0.0000	0.0829
0.0000	0.0000	0.0000	0.0000	0.0829
0.0000	0.0000	0.2109	0.0000	0.1216
0.0000	0.2468	0.0000	0.0000	0.1216
0.0000	0.2472	0.0000	0.0000	0.1216
0.0000	0.0000	0.1925	0.0000	0.1216
0.0036	0.2473	0.0000	0.0000	0.1216
0.0302	0.2475	0.0000	0.0000	0.0518
0.0000	0.0000	0.0000	0.0000	0.0518
0.0000	0.2466	0.0000	0.0000	0.0518

Table 2
Energy Matrix for Ancillary Services Provided by the Battery for Case 1.

Frequency Regulation [kWh]	Voltage Regulation [kWh]	Transformer Power Demand Regulation [kWh]	Idle [kWh]	Recharge [kWh]	Recharge by Excess PV Power [kWh]
0.0479	-5.7500	0.0000	0.0000	0-9.45	0.0000
0.0000	-5.7500	0.0000	0.0000	0-9.45	0.0000
0.0000	-5.7500	0.0000	0.0000	0-9.45	0.0000
0.5303	-5.7500	0.0000	0.0000	0-9.45	0.0000
0.4504	-5.7500	0.0000	0.0000	0-9.45	0.0000
0.4408	-5.7500	0.0000	0.0000	0-9.45	0.0000
0.0767	-2.8750	0.0000	0.0000	0-9.45	0.0000
-0.1821	0.0000	0.0000	0.0000	0-9.45	0.0000
0.0000	-2.8750	0.0000	0.0000	0-9.45	0.0000
0.0000	-2.8750	0.0000	0.0000	0-9.45	0.0098
0.0000	0.0000	0.0000	0.0000	0-9.45	0.3000
0.0000	0.0000	0.0000	0.0000	0-9.45	0.6739
0.0000	0.0000	0.0000	0.0000	0-9.45	0.7623
0.0000	-2.8750	0.0000	0.0000	0-9.45	0.3730
0.0000	-2.8750	0.0000	0.0000	0-9.45	0.0822
0.0000	0.0000	0.0000	0.0000	0-9.45	0.0000
0.0000	0.0000	-2.8750	0.0000	0-9.45	0.0000
0.0000	-5.7500	0.0000	0.0000	0-9.45	0.0000
0.0000	-5.7500	0.0000	0.0000	0-9.45	0.0000
0.0000	0.0000	-2.8750	0.0000	0-9.45	0.0000
-0.0128	-5.7500	0.0000	0.0000	0-9.45	0.0000
-1.1372	-2.8750	0.0000	0.0000	0-9.45	0.0000
0.0000	0.0000	0.0000	0.0000	0-10.8	0.0000
0.0000	-2.8750	0.0000	0.0000	0-10.8	0.0000

Table 3
Simulation Runtime and Cost Values by Using Different Parameters for Case 1.

# of Iterations	# of Search Agents	Cost	Time (s)
10,000	30	-6.0933	0.75
10,000	50	-5.8501	1.20
100,000	30	-6.5997	6.91
100,000	50	-6.7455	11.35
1,000,000	30	-7.1860	69.11
1,000,000	50	-7.3280	115.01
2,000,000	50	-7.4587	228.35

Results of the simulations for given cases are given in **Table 4**. These simulations show that planning a day with different ancillary services generates better results. Our profits were around 7.4 USD for extreme days, and for an average day, our profits were around 2.88 USD. Under the given market conditions, yearly profit would be approximately 1050 USD, for an average day. This profit, combined with the profit of the distribution network operator, may be better in the coming years with additional regulatory frameworks.

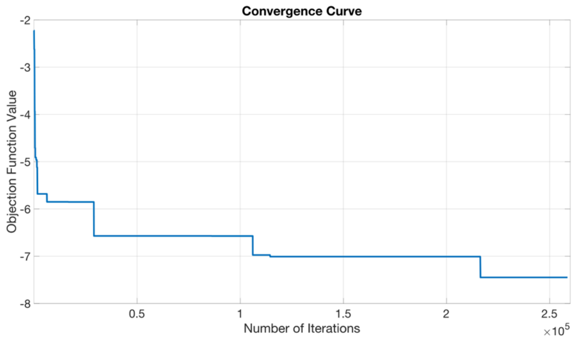

Fig. 14 – *Convergence Curve for Case 1 with 250000 iterations.*

According to **Table 4**, when Case 1 is compared with Cases A, B, and C, the revenue of the battery participation to all ancillary services is 1622% higher than the revenue of the battery participation to only frequency service, 16.76% higher than the revenue of only overvoltage service, and 711.88% higher than the revenue of only demand service. That means the multiple ancillary service action is more profitable than the one ancillary service action.

Table 4
Simulation Results for Different Cases.

Case	Profit ($)	Cost
1	7.4587	-7.4587
2	7.3280	-7.3280
3	2.9006	-2.9006
4	2.8710	-2.8710
A	0.4332	-0.4332
B	6.3878	-6.3878
C	0.9187	-0.9187

The decision-making process of the battery for two different cases can be seen in Fig. 15. The change of the SoC of the battery for two near optimal cases is illustrated in Fig. 16. Figures show that the SoC is kept within the allowed limits between 20% and 80%. Moreover, as aimed, the initial 80% SoC for the start and end of the day is kept at the same level.

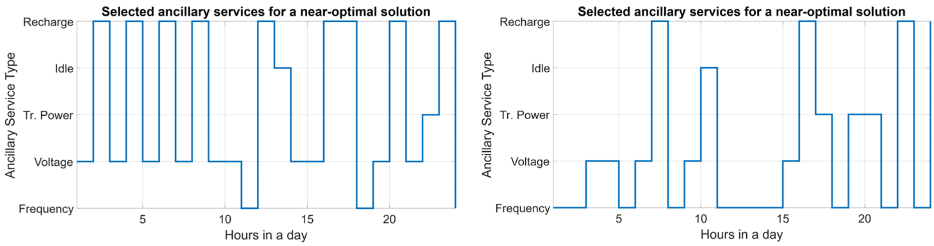

Fig. 15 – *Decision Making for Near-Optimal Solutions: Case 1 and 4.*

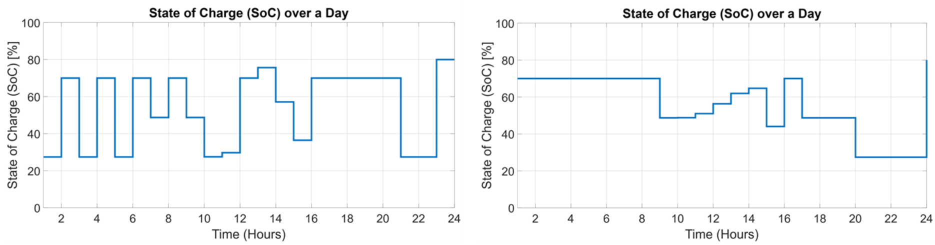

Fig. 16 – *State of Charge for Case 1 and Case 4.*

6 Conclusion and Future Works

This study considers ancillary services from the perspective of a battery owner. We utilized a grey wolf optimization-based approach to maximize the profit of the battery owner based on the available market conditions. The battery-to-grid simulations were performed by contributing ancillary services such as frequency regulation, voltage regulation, and transformer power demand regulation. Moreover, when not needed, the case of being idle, and when required, recharging options were considered. This approach aims to improve the profits of the battery owners by letting them participate in ancillary services; at the same time, this participation improves the operation strategies of the distribution network operators. From the simulation results, we observed that the battery owner could obtain a yearly profit of around 1050 USD based on the market conditions. With improved regulatory frameworks, this amount may be improved more. Future studies can focus on the considering power network constraints with improved operation strategies, multiple provisions of a larger variety of services batteries can provide and investigating the long-term benefits and drawbacks of regular participation in multiple flexibility markets.

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